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An Efficient Deep Learning Approach for Plant Disease Detection

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Abstract- During the stages in which plants are growing, they are more likely to be infected by a variety of diseases. Because of insufficient laboratory facilities and a dependance on the knowledge of specialists, initial plant disease identification is a time-consuming process. If the diseases are not discovered in their early stages, then it is possible that they will have a negative impact on the overall yield, which will lead to a reduction in the profits made by the farmers. Several studies have discussed various state-of-the-art systems that are based on Deep Learning as well as Machine Learning methodologies in an effort to find a solution to this issue. On the other hand, the majority of such systems either employ large numbers of input variables or even have poor accuracy in their classifications. In this paper, an innovative combined approach for automatic detection of plant diseases is proposed. The model is based on Variational Autoencoder (VAE) networks and Convolutional Neural Networks (CNN). Techniques for the automated detection of plant diseases offer a number of benefits, including the simplification of the lengthy process of observing large agricultural farms and the identification of disease symptoms at an early stage. In this work, the proposed combined approach is utilized to detect the disease known as Bacterial Spot that is present in plants by utilizing the leaf images of those plants. The proposed method achieves an accuracy rate of 98.85 percent when used for testing and 99.17 percent when used for training.

Keywords— Convolutional neural network, Deep learning, Intelligent models, Plant disease, Variational Autoencoder.

I.INTRODUCTION

When plants are in their diverse growth stages, they, like people, are vulnerable to a wide variety of diseases. As a consequence of this, the overall crop yield and, as a direct result of this, the farmer's profit margin is both negatively impacted. The identification of plant diseases at an early stage is essential in order to find a solution to this problem. The detection of plant diseases through manual inspection can be carried out either by agricultural experts or by farmers. Having said that, this is a really difficult and task is time-consuming to complete. Many researchers from different parts of the world have come up with innovative solutions to this issue by discussing various state-of-the-art processes for automatically detecting plant diseases. These systems make use of a variety of Deep Learning and Machine Learning techniques. These cutting-edge systems make use of an extremely large number of different training parameters. As a direct consequence of this, the amount of time required for training and prediction by these systems is extremely extensive, or else a machine with a high level of computation power is required. Through the application of the VAE network, this analysis endeavor makes an effort to cut down on a lot of features that are used for prediction, all while attempting to maintain a high degree of accuracy in the classification of plant diseases. This, in turn, reduces the total quantity of training constraints by an important factor, which in turn results in a reduction in the total amount of time required for training and prediction.

Recent developments in computer vision have opened up the possibility of developing and improving the concept of precise plant disease detection as well as continuing to expand computer vision's applications in the field of smart agriculture. The identification and categorization of plant diseases is accomplished through the utilization of overall image processing techniques such as texture analysis and contrast enhancement. A variety of methods, some of which are more common than others, are discussed here as approaches for identifying plant diseases. In order to accomplish efficient feature extraction, these procedures can be incorporated into a variety of different image pre-processing techniques. An artificial neural network (ANN) is a data analysis model that is used in machine learning and cognitive science. It is induced using the human nervous system. The human brain is made up of many neurons that are connected to one another and work together to solve specific problems. Before the invention of deep learning (DL) models, a number of studies focused on developing disease detection models that made use of image processing and feature extraction. The most significant challenge presented by this prototype is the complexity of trying to define the signs for identification using computers. This challenge has been overcome by the utilization of DL models, which do not require the features to be defined; rather, it learns the features through the application of optimization.

The capability of DL models to attain different degree of quality on laboratory images has been used in a number of different works. Maximum accuracy can be achieved by validating the specific classification models on data that is similar to the training data. This allows for the greatest possible precision. A significant number of the previously published works have made use of DL models to diagnose diseases. These models have been trained and validated using the Plant Village dataset, which includes a fixed number of variables with the same background. Recent research has looked into how well deep learning models perform when trained on individual leaves and sites. In this paper, a novel combined approach for automatic detection of plant diseases focused on VAE and CNN is proposed. This model has smaller training dimensions than other systems that are currently available in the literature.

The remaining sections of the paper are arranged in the following manner. The previous works are summarized in section 2, and the combined approach that is being proposed is presented in section 3. After that comes the result analysis in section 4, which is followed by the conclusion in section 5.

II. Related Work

In order to recognize a variety of patterns, a large number of researchers investigated several approaches based on Machine Learning [1], Deep Learning [2], Image Processing [3], and the Semantic Web [4]. This section describes several cutting-edge technologies that are now available in the existing papers that are utilized for automated detection of disease in plants. One of the most fundamental and important operations in agriculture is the diagnosis of plant diseases. Identification is often conducted manually, physically, by molecular biological testing, or through microscopy the majority of the time. The difficulty with using a visual examination to diagnose illnesses is that the person doing the examination is taking on a subjective task, which makes them susceptible to cognitive and psychological processes that really can result to bias, visual stimuli, and, error.

Srdjan et al. [5] introduced an innovative model for the detection and classification of plant leaf diseases by utilizing deep CNN (DCNN). Training and straightforward application in practice are both accomplished with the help of the DCNN model. The improved approach is capable of distinguishing plant leaves from their environments and also can discover thirteen various types of plant illnesses largely dependent on healthier plants. Guo et al. [6] developed a method for the diagnosis and detection of plant diseases that is dependent upon DL and improves the generalization, learning, and precision performance of the method. In the beginning, the region proposal network (RPN) is utilized for the purposes of localizing and identifying the leaves in an environment that is complex. The RPN technique's results will then determine how the picture will be segmented in the following step.

The use of neural networks (NNs) to accomplish the overarching objective of precise plant protection through the utilization of hyperspectral data is garnering an increasing amount of interest. The notion of spatial and temporal variability is the foundation of precision plant protection, which provides an all-encompassing method for the management of plant diseases. NNs were mostly utilized in the past for the purpose of data mining; however, recent applications including hyperspectral data have demonstrated significant potential for the early diagnosis of illness. It possesses one-of-a-kind qualities such as learning, generalization, and creativity, which enables it to assist in the accurate identification of plant diseases. The degree to which NNs can be diagnosed is far higher than those of other machine learning approaches.

One of the most difficult challenges faced in today's world is the processing of massive amounts of data consisting of high-dimensional hyperspectral imageries. For the purpose of handling hyperspectral data, dimensionality reduction is an application that is both significant and efficient. It has been stated that a high level of document dimensionality reduction might be accomplished with maintaining a satisfactory classification accuracy in hyperspectral data. Since it is common knowledge that hyperspectral information include both visible and underlying spectral information, neural networks are required in order to evaluate the potential and achievements of this type of data.

Deep Convolutional Encoder Networks were proposed by Khamparia et al. [7] as a method for the detection of diseases affecting seasonal crops. They looked at 900 different leaf photos from three different crops: maize, potato and, tomato which were organized into six different classifications. They were successful in training with an accuracy of one hundred percent, however the measure efficiency of their model was only 86.78 percent. Because the accuracy of the model during training was significantly greater than the accuracy of the model during testing, there was a possibility that perhaps the model to be trained overfit data of training. They also noted that their system employed about three million training model parameters in their article, which is a significantly bigger amount than the training parameters that were used in the work that was proposed. They have been successful in identifying seasonal agricultural diseases by utilizing Autoencoder and CNN.

With the use of CAE and Support vector machine (svm), Pardede et al. [8] developed a system that is capable of performing automatic disease detection on maize and potato crops. From the PlantVillage collection, they retrieved photos of the corn and potato plant's leaf surfaces. They were accurate 87.01 percent of the time when identifying illnesses in potato plants and 80.42 percent of the time when detecting infections in maize plants. And from the other perspective, the VAE and CNN models are the foundation of the innovative prediction approach that was developed. In addition to this, the model that was proposed obtains a testing accuracy that is greater than the testing accuracy that was achieved by the model that was proposed by Khamparia et al [7].

III. PROPOSED WORK

Fig. 1 provides a visual representation of the system architecture of the combined approach. The instance shown in the figure illustrates how the input image of a plant leaf is originally introduced into the VAE after the image has been preprocessed and its quality enhanced. In VAE, the image of a real plant leaf is first transferred via an encoder network, where it is converted into an optimal distribution of data. The next step is for this distribution of data to be sent to a decoder network, where it is used to build a new image of a leaf. An autoencoder model is trained if there is a sufficient degree of similarity between the image of the resulting leaf and the actual leaf. Next, the CNN approach is utilized to obtain an useful collection of features and to appropriately categorize the presence of the diseases with their respective class labels. The next subsections will offer an in-depth explanation of how each of these procedures really works [8, 9].

Convolutional neural network

A feed-forward neural network, also known as a convolutional neural network, is typically employed for the purpose of analyzing visual images through the processing of data using a grid-like structure. Features in an image can be recognized and categorized with the assistance of a convolutional neural network. Instead of doing a straightforward matrix multiplication, the Convolutional Neural Network (CNN) method of Deep Learning employs the convolution operation. CNN is the most effective method for dealing with images when compared towards the other Deep Learning approaches. It does this by extracting various temporal and spatial features from the images that are sent into it. These features play an important part in image categorization as well as other tasks like computer vision [10,11].

The term "convolution" refers to an operation that is expressed as a binary association of two real-valued functions, such as a(x) and b(x). It is possible to give a mathematical definition for it using the (1) in the continuous domain. In a similar manner, the mathematical model for the convolution process may be stated as (2) when it is performed in the discrete domain.

$$a(x) * b(x) = \int a(x).\, b(x-j) d_j \qquad (1)$$

$$a(x) * b(x) = \sum_{k=-\alpha}^{\alpha} a(x).\, b(x-j) \qquad (2)$$

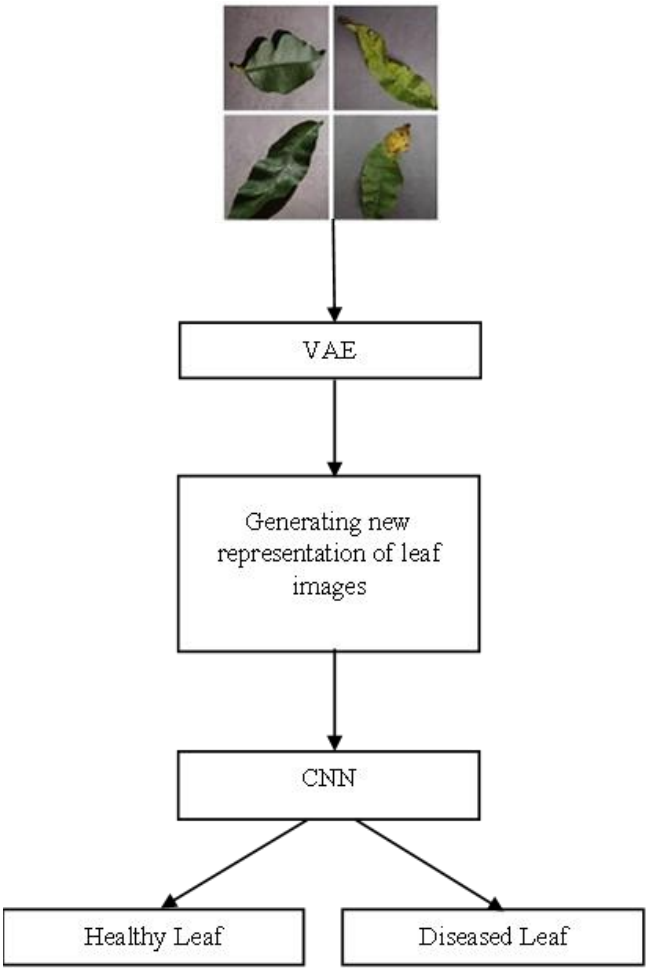

Fig. 1. Architecture of the proposed combined approach.

In a CNN, a(x) and b(x) are referred to as the input as well as filter/kernel, accordingly, and the feature map is the outcome of the convolution process. a(x) and b(x) are both represented by the notation x. Multidimensional arrays are used to hold the input, the filter/kernel, and the feature map respectively. It is possible to deduce from the specification of the operation of convolution that the size of the feature output map will be$i - j + 1 \times i - j + 1$times the size of the matrix input if the matrix inputsize is $i \times i$ and the size of the kernel is $j \times j$(where $j \leq i$) respectively. Therefore, it is possible to draw the conclusion that the output size of the feature map is reduced following each convolution process. In other words, after each iteration of the convolution procedure, the size of the input picture is reduced until it reaches zero, and then it continues to decrease. Therefore, it restricts the amount of depth a CNN can achieve by setting a maximum limit on the number of convolutional layers that may be found in a CNN. In addition, the components that are located on the edges and corners of the matrix input are employed far less frequently than the other elements that are existing in the matrix's center. Padding is utilizedby the Convolutional layers that are part of the CNN in order to address both of these concerns [12].

The matrix input is made larger by the use of padding, which involves adding layers of zeroes to the boundary of the matrixinput. In this way, the area of the matrix input that has to have the convolution operation done on it is raised, which guarantees that perhaps the representation of the matrixinput will not decrease after the convolution operation has been conducted. By adding several padding layers, this not only guarantees that the elements that are present on the edges and corners are also employed, but it also ensures that they are utilized. Valid padding as well as the same padding are the different kinds of padding that are available. In the process known as Valid Padding, no more layers of zeroes are added to the matrix input. As a result, the dimensionality of the output matrix stays the same as it was before, i.e., it has $i - j + 1 \times i - j + 1$. The Same Padding method, on the other hand, involves adding p layers of zeroes to the matrix input in order to maintain the same dimensionality of the matrix after the convolution process has been performed. The value of p may be calculated using (3). The design of the proposed combined approach is accomplished with the usage of the same padding.

$$i + 2p - j + 1 = i \Rightarrow p = \frac{j-1}{2} \qquad (3)$$

Variational autoencoder

A variational auto-encoder is, in the broadest sense, a deployment of the continuous latent variable model, which is a more generic statistical framework. Although this work utilized variational auto-encoders to build a latent space of shapes, it have a broad range of applications, such as the generation of images, videos, or shapes.

VariationalAutoencoder (Kingma& Welling [9]), abbreviated as VAE, is a notion that is really less comparable to all of the autoencoder models that is strongly based in the methodologies of variational bayesian and graphical model. In this work it map the input into a singular fixed vector; rather, map it into a distribution. Let's call this distribution p_θ and the parameter that describes it will beθ. The following statements provide a complete definition of the connection between the data input x and the latent encoding vector z. Prior $p_\theta(z)$,Likelihood$p_\theta(x|z)$, Posterior $p_\theta(z|x)$.

The value of parameter θ that optimizes the chance of producing realistic data samples should be considered the best value.

$$\theta^* = \underset{\theta}{\arg max} \prod_{i=1}^{n} p_\theta(x^{(i)}) \quad (4)$$

$$\theta^* = \underset{\theta}{\arg max} \sum_{i=1}^{n} log p_\theta(x^{(i)}) \quad (5)$$

Let us now revise (5) in order to more clearly show the data construction process by incorporating the encoding vector.

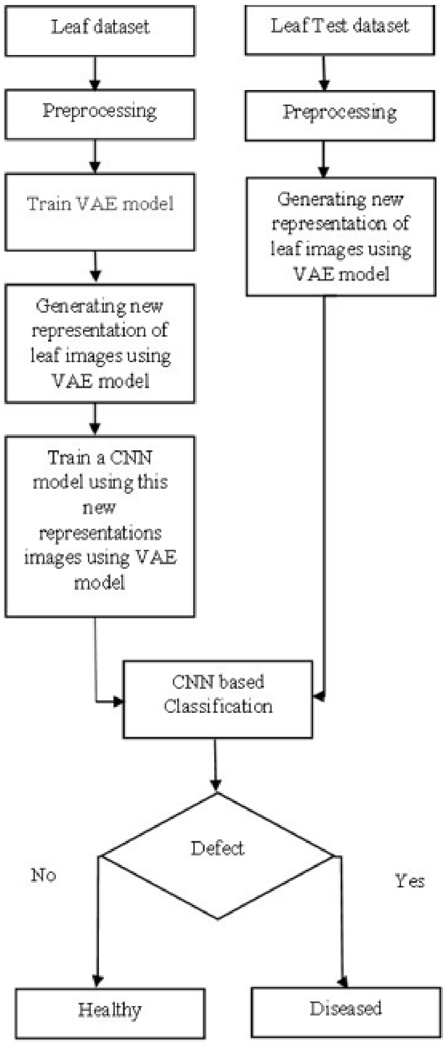

Fig. 2. Proposed workflow to illustrate the methodology.

$$p_\theta(x^i) = \int p_\theta(x^{(i)}|z) p_\theta(z) dz \quad (6)$$

In addition, the flow chart that illustrates how the suggested process might work may be represented in Fig. 2. Here the leaf dataset collected is preprocessed and trained via a VAE model. The VAE model generate a new representation of leaf images. And that will be fed as an input to the CNN for classification. In the test phase, the test data is fed into the system after preprocessing to remove the noise. Then the generated new representation of leaf images by VAE model is fed to CNN for classification. The CNN classifier will predict the leaf as diseased or healthy.

IV. RESULT ANALYSIS

In this part, the performance of the proposed combined approach for detecting plant diseases is evaluated using a benchmark dataset consisting of plant leaf diseases. The outcomes of the experiment are analyzed in terms of a variety of parameters and measurements. In the following sections, you will find details associated with the implementation as well as the analysis of the findings. The VAE and CNN based proposed combined approach is tested on a computer with an i7-1165G7 processor, Intel Iris Xe Graphics, 16 GB of RAM, and a 512GB Solid State Drive. Python 3.10 is the tool for implementation. The combined approach is evaluated in comparison to a benchmark dataset consisting of leaf diseases.

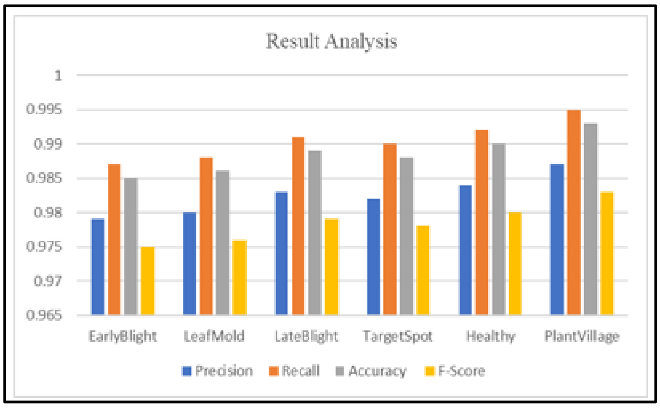

Fig. 3. Analysis of the results using the combined approach with distinct measures.

As show in Fig. 3 is an evaluation of the classification results obtained by using the combined approach model of VAE and CNN model to the leaf image dataset. The results make it abundantly known that the combined approach model of VAE and CNN model has successfully produced successful results on the datasets that was utilized. For example, the combined approach model of VAE and CNN has a precision of 0.978, recall of 0.986, accuracy of 0.984, and an F-score of 0.974 when it comes to classifying the condition known as "Early Blight dataset." In the result, the combined approach model of VAE and CNN is able to classify the disease known as "Late Blight dataset " with a precision of 0.983, a recall of 0.991, an accuracy of 0.989, and an F-score of 0.979. In the meanwhile, the combined approach model of VAE and CNN has a precision score of 0.980, a recall score of 0.988, an accuracy score of 0.986, and an F-score of 0.976 when it comes to classifying the disease known as "Leaf Mold dataset." In addition, the combined approach model of VAE and CNN has a precision of 0.982, recall of 0.99, accuracy of 0.988, and F-score of 0.978 when it comes to the classification of the disease known as "Target Spot dataset." The combined approach model of VAE and CNN has a precision of 0.984, recall of 0.989, accuracy of 0.991, and F-score of 0.981 when it comes to classifying the disease known as "Healthy dataset". Last but not least, the combined approach model of VAE and CNN has a precision of 0.987, recall of 0.995, accuracy of 0.993, and F-score of 0.983 when it comes to classifying the disease known as " PlantVillage dataset".

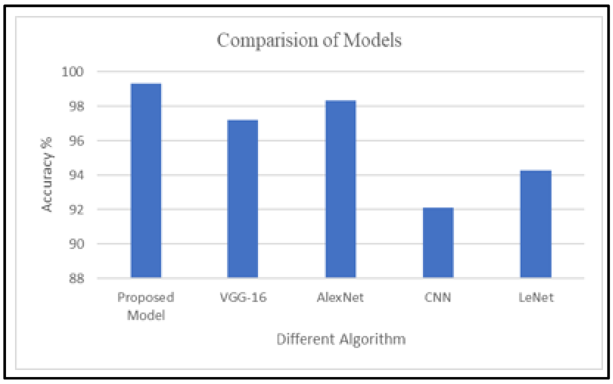

Fig. 4. Comparative analysis of proposed model with existing models.

Fig. 4 present a quick comparison and analysis of the findings obtained by the combined approach model of VAE and CNN with those obtained by more current approaches. According to the findings, the CNN approaches produced the poorest results, with an accuracy of just 0.921 respectively. At about the same time, the Lenet technique has achieved a value of 94.4 for its accuracy that is considerably higher than before. In addition, the VGG-16 model and AlexNet model, shown moderate results, with an accuracy of 0.972 and 0.983 respectively. Despite this, the combined approach model of VAE and CNN algorithm that was proposed was able to achieve maximum performance while maintaining a greater accuracy of 0.993.

It is clear from the figures that have been shown so far that the combined approach model of VAE and CNN model is identified to be an acceptable technique for the detection of plant leaf diseases in an environment that is real-time.

V. CONCLUSION AND FUTURE WORK

In this paper, an automated approach for the identification and classification of plant leaf diseases utilizing the combined approach model of VAE and CNN model was proposed. The combined approach model of VAE and CNN model's objective is to identify the presence of plant diseases through the utilization of leaf images that have the highest possible detection rate. In order to assure that the combined approach model of VAE and CNN model will function in the most effective manner possible, a thorough computation analysis will be carried out. The outcomes of the experiments have revealed some encouraging findings for the combined approach model of VAE and CNN model when compared to the most recent state-of-the-art approaches in terms of the various metrics. In the near future try to implement a model with less loss and computational cost.

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